**From task-general to task-specific cognitive operations in a few minutes:
Working memory performance is an adaptive process**

Running head: From task-general to task-specific

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Abstract

Measurement of cognitive functions is typically based on the implicit assumption that the mental architecture underlying cognitive task performance is constant throughout the task. In contrast, skill learning theory implies that cognitively demanding task performance is an adaptive process that progresses from effortful and task-general metacognitive and control processes to more automatic and task-specific performance. However, this hypothesis is rarely applied to the short time spans of traditional cognitive tasks such as working memory (WM) tasks. We utilized longitudinal structural equation models on two well-powered data sets to test the hypothesis that the initial stages of WM task performances load on a task-general g-factor and then diverge into factors specific to task structure. In line with the hypothesis, the first experiment (N = 296) indicated perfect correlation between WM paradigm-specific latent factors in the beginning of the task, after which their intercorrelations diverged. The second experiment (N = 201) replicated unity between all except one paradigm-specific latent factor in the beginning of the task, followed by divergence. These results can be interpreted in the skill learning framework as suggesting that the mental architecture underlying complex cognitive performance progresses rapidly from initial engagement of task-general cognitive processes towards task-specific ones. This has several important implications for the measurement of complex cognitive functions.

Keywords: Working memory, skill learning, longitudinal structural equation modeling, latent structure, cognitive architecture, construct validity, reliability, cognitive task dynamics

1. Introduction

Survival requires adaptation: according to Spencer (1855), the “fundamental condition of vitality is that the internal order shall be continually adjusted to the external order” (§173). On this line of reasoning, cognition is an adaptive process. Novel tasks call for adaptive behavior that is thought to rely on successful executive control (Miller & Cohen, 2001; Miyake et al., 2000; Norman & Shallice, 1986). While adaptivity and learning are considered to be cornerstones of human cognitive ability (Anderson, 2014; Chein & Schneider, 2012), the outcome measures of complex cognitive task performances typically sum up the whole task period into single scores. This entails a static view of the mental architecture underlying task performance. Anderson (2014) calls this the *componential computational theory of mind*, which implies that the mind consists of dissociable functions that can be measured with cognitive tasks. For example, the Stroop task arguably “taps on” a person’s inhibitory capacity and the n-back task is considered to tap on their working memory updating capacity. Considering cognition as an adaptive process is a radical departure from this approach: it entails that performing a cognitive task alters what is being measured, because the cognitive system adapts to the testing context. Thus, what is measured by a task is partly created by the measurement situation, rather than being “out there” on the latent level, waiting to be measured. This way of thinking motivates examining cognitive performance as a dynamic process that evolves over time.

The skill learning approach (e.g., Ackerman, 1988; Chein & Schneider, 2012; Schneider & Chein, 2003; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977) espouses this general view, by focusing on the adaptivity of cognition instead of static mental architecture. It is based on a long research tradition on slow and effortful vs. fast and automatic cognitive systems. The skill learning approach is often applied to explain learning in perceptual-motor tasks or tasks that require problem solving. In the present study, we apply it to complex cognitive task performance, namely working memory (WM) tasks. Besides involving perceptual-motor processes, the cognitive demands and unfamiliarity of WM tasks call for executive resources needed for strategy generation and implementation (e.g., Waris, Fellman, Jylkkä, & Laine, 2020; Waris, Jylkkä, Fellman, & Laine, 2021). In this way, they can be considered as analogical to any cognitively demanding novel task that requires skill to be performed efficiently. The skill learning approach entails that processing of novel tasks proceeds from task-general metacognitive and control processes to task-specific, more automatic processes (Taategen, 2013). Metacognitive processes include the generation of a suitable strategy for the task while the controlled execution phase involves its effortful and controlled implementation. In turn, automatization proceeds gradually with task exposure and frees the effortful processes to other tasks (Chein & Schneider, 2012).

Applying the skill learning approach to the psychometric context implies that what is being measured can change as the participant develops a skill to perform the task. Consider a complex WM task like the n-back, where the participant sees stimuli that are constantly changing. During each new stimulus, the participant needs to decide whether the stimulus is the same as the one that was presented n trials ago. For example, in a 2-back task with the series 2-5-1-**5**-4-3-**4**, the subject should press the response button corresponding to “same”

during the bolded trials (Kirchner, 1958). The participant assumedly enters the metacognitive phase already upon receiving task instructions (wondering what the task will be like, trying to remember the stimulus-response mappings and task instructions, planning a strategy, etc.). Thus, cognitive processes responsible for task performance start even before the first trial. The memorized task instructions and self-generated strategies are effortfully implemented in the beginning of a task, but with continued performance, processing is gradually automatized. With increasing automatization, the relative contribution of executive control is expected to diminish. If the cognitive processes engaged by the task evolve in time, it can be questioned whether a cognitive task relies on a fixed constellation of cognitive processes, which is at least an implicit assumption when operating with the often-used summative scores in cognitive testing. Rather, following the skill learning view (Chein & Schneider, 2012), we hypothesize that a demanding cognitive task relies on different processes depending on the stage of learning, and that such changes can take place already during the brief time spans (minutes) that these tasks usually take.

The assumption that the later stages of task performance serve to consolidate task-specific skills receives support from the cognitive training literature, albeit there the time scales span from hours to weeks, rather than minutes. Prolonged training on a cognitive task typically does not yield transfer to other types of tasks, but rather enhances performance only in tasks that have close structural resemblance to the trained task (Kassai, Futo, Demetrovics, & Takacs, 2019; Melby-Lervåg et al., 2016; Melby-Lervåg & Hulme, 2013; Sala & Gobet, 2017). For example, n-back training with digit stimuli can clearly enhance performance on a untrained n-back task with letters, but not on structurally dissimilar WM updating tasks such as a running memory task (Gathercole, Dunning, Holmes, & Norris, 2019; Soveri, Antfolk, Karlsson, Salo, & Laine, 2017). This lack of transfer could be explained by considering cognition as an adaptive process, where performance on a repeated task starts to automatize and rely on task-specific subroutines instead of task-general processes (Fellman et al., 2020). Also, the functional brain imaging studies of WM training, showing modulations of activity in large-scale brain networks associated with cognitive and perceptual-motor systems, are consistent with the skill learning context: Activity in the dorsolateral prefrontal cortex as well as parietal and sensory areas, initially responding to high cognitive load, attenuates over the training period, while activity of the striatum that is involved in executing learned sequences increases (Salmi, Nyberg, & Laine, 2018).

In the present study, we examined the evolvement of task paradigm-based latent structure of commonly used WM tasks within the short time span of a single testing session that took ca 5 to 14 minutes per task. This was motivated by neuroimaging evidence indicating that the brain systems underlying WM begin to adapt already during one testing session (e.g., Badre, Kayser, & D'Esposito, 2010). Another line of evidence for the dynamic nature of the cognitive processes underlying within-session WM performance comes from self-reported strategies that are also reliably associated with objective WM performance (Fellman et al., 2020; Forsberg, Fellman, Laine, Johnson, & Logie, 2020; Laine, Fellman, Waris, & Nyman, 2018). Of particular relevance here is a recent microgenetic study (Waris et al., 2021) that analyzed the block-by-block evolvement of strategy use within a single n-back test session. About half of the participants reported using a self-generated strategy already during the very first task block, and changes in selected strategy were most common during

the initial task blocks, after which strategy use became more stable. The generality of this pattern in strategy development was corroborated by a similar study that successfully replicated these findings with quite different episodic memory tasks (Waris et al., 2020). The findings of these two microgenetic studies fit well to the skill learning view, according to which strategy generation and controlled execution, representing task-general executive resources (the g-factor), are most prominent at the initial stages of task performance. Importantly, they indicate that changes in the allocation of cognitive resources do not require a longer practice period, such as in WM training, but can be observed even in a single test session, i.e., within a few minutes.

To test the assumption that the cognitive processes underlying WM task performance are not static but change during the short time period that such tasks usually take, we utilized longitudinal structural equation modeling (LSEM) which enables assessing the same psychometric constructs at several time points (see Little, 2013). We thus examined how the covariances between paradigm-specific latent factors change over four consecutive time points, all within one testing session. Our hypothesis was that the latent factor correlations would show a change from unity to diversity. We used pretest data from two previous preregistered WM training experiments to replicate the results with two datasets (Fellman et al., 2020; Ritakallio et al., 2022). The WM task paradigms employed as pretest measures were n-back, running memory, simple span, and selective updating, with partly different task constellations in the two experiments. Each WM paradigm included task variants that employed different stimuli.

As noted above, we used models where the latent factors corresponded to the WM task paradigms (three or four WM task paradigms, each with two to four task variants). As the cognitive skill learning hypothesis implies that the processing of novel tasks evolves from task-general, global, and united to more task-specific, modular, and diverse, we expected to see a decline in the latent factor correlations over time in LSEM. To test this, we constrained the latent factor correlations in two ways. First, we examined whether it is possible to constrain the different paradigm-specific factors to correlate at one without worsening model fit. Our hypothesis was that this can be done at the initial but not in the final stage. If all the paradigm-specific factors can initially be constrained to correlate with each other at one, this indicates that at the outset of the WM tasks, they behave as a single construct. Second, we examined whether the latent factor intercorrelations could be constrained to be equal across the time points. Our hypothesis dictates that the intercorrelations are not equal across time, as the initial correlations at one should weaken, indicating an evolvement from a single construct to a gradual separation of the paradigm-specific factors. In sum, our hypothesis was that within the short time span of single test sessions, the intercorrelations between the paradigm-specific latent factors show a changing pattern from unity to diversity. This contrasts with the influential model of Miyake et al. (2000) which suggests a constant factor structure indicating both unity and diversity.

2. Experiment 1

In this experiment, we tested the main hypotheses with data from an Internet-based WM training study. To examine the underlying cognitive architecture of WM processing

when the tasks are novel, we focused solely on pretest performances. The duration of the tasks was comparable to that used in cognitive testing generally (on average 5 – 14 minutes each). The data used in the analyses is available at <https://osf.io/gvqhu/>.

2.1 Participants and procedure

The current data stems from the pretest of an online randomized controlled trial that examined WM training and its mechanisms (Fellman et al., 2020; preregistration at <https://aspredicted.org/r7qs9.pdf>). The study was approved by the Institutional Review Board of the Departments of Psychology and Logopedics, Åbo Akademi University, and it was conducted in accordance with the Helsinki Declaration. In that study, 419 participants were recruited through Prolific Academic (<https://www.prolific.co/>). Of these, 296 participants were included in the present study after excluding those that did not meet our inclusion criteria ($n = 117$), and those that reported cheating during task performance ($n = 6$). Our inclusion criteria were English as native tongue, no current psychiatric or neurological illnesses that affected daily life, no current use of central nervous system (CNS) medication, no current psychotropic drug use (except tobacco, alcohol, and cannabis), and no intoxication at the time of testing. The participants were 18–50-year-olds with a mean age of 34.08 years ($SD = 8.52$), and 62.50 % ($n = 185$) were females. The mean length of education in the sample was 15.80 years ($SD = 3.49$).

2.2. Materials

The eight WM tasks included in this study encompassed four n-back tasks (separate tasks with digits, letters, colors, and boxes as stimuli), four Simple span tasks (Forward simple spans with digits and boxes, Backward simple spans with digits and boxes), and two Running memory tasks (digits and boxes). All data were from the pretest of the original experiment when the participants saw these tasks for the first time (Fellman et al., 2020).

N-back. We employed four adaptive single n-back tasks: with digits (1 to 9), letters (A to I), colors (blue, yellow, red, green, purple, black, pink, orange, and gray), and locations (boxes presented in a 3×3 matrix) as stimuli. The items in each n-back task variant were presented one at a time on a computer screen, and the participants were instructed to respond “yes” or “no” to each item with a computer keyboard press, indicating whether or not the current item corresponded to the item presented n items back in the sequence. Each n-back variant consisted of 12 blocks of n-back, with each block containing $20 + n$ trials. Out of the 20 trials in a block, six were targets and 14 non-targets. Four of the non-targets were lures (i.e., identical to the target items except that they were presented $n \pm 1$ back) to increase the task demands. Stimulus display time for each item in a sequence was 1500 milliseconds, whereas the interstimulus interval was 450 milliseconds. The n-back tasks were adaptive so that task difficulty depended on individual success rate. Each n-back task started with a 1-back block, and the level of n could vary between 1 and 12. If the participant recalled 18–20 trials correctly in a block, the program increased n by one. The level of n remained the same if the participant recalled 15–17 trials correctly, while 5 or more incorrectly recalled trials resulted in a decrease of n by one. The length of these tasks was ca 14 minutes each. There were no practice trials because the task started at the easiest level, that is, 1-back.

Span. We administered four simple span tasks: two Forward span tasks and two Backward span tasks. One of the forward spans used digits as stimuli (Forward simple span with digits; FSD), whereas the other employed visuospatial locations (Forward simple span with boxes; FSB). In both variants, the participants completed one trial of each list length, with the length of the randomized lists ranging from 4-10 in FSD and 3-9 in the FSB. We also administered two Backward simple span tasks, one with digits (Backward simple span with digits; BSD), and the other one with locations (Backward simple span with boxes; BSB). The list lengths ranged from 3 to 9 in both Backward span variants, and the item sequences were presented in a randomized order. As in the Forward simple span tasks, the participants were to recall one sequence per list length. Both the Forward and Backward simple span task had the same stimulus presentation time, with a 1000 millisecond item exposure time and 500 millisecond inter-stimulus intervals. The length of these tasks was ca 5 minutes each. There were three to seven practice sequences, depending on the participant's performance. The last of the practice sequences was longer (nine items) and the rest were shorter (four to five items). If the participant answered two consecutive short sequences correctly, they proceeded to the longer sequence, after which the actual task commenced irrespective of whether the longer sequence was answered correctly.

Running memory. The test battery included two Running memory tasks where the participants were prompted to recall a given number of last items from a suddenly aborted sequence. One of those was a Running memory task with digits (RMD) whereas the other one was a Running memory task with boxes (RMB). In both variants, stimulus presentation time was 1000 milliseconds and interstimulus interval was 500 milliseconds. In RMD, digit sequences with unpredictable length were shown on the screen, after which the participant was to recall the last four items in the correct order. The RMB was otherwise identical to the RMD, but the stimuli were spatial locations presented in a 3×3 matrix. In both task variants, the participant completed eight trials in a randomized order, with item sequences ranging from 4 to 11 items (i.e., one trial of each list length). The length of these tasks was ca 6 minutes each. There were two to six practice sequences, depending on the participant's performance. If the participant answered two consecutive sequences correctly, they proceeded to the actual task.

2.3. Dependent variables

To examine the changes in factor structure over time, we split the task blocks into four phases, roughly matched in length. This was done to attain a balance between having enough observations to enable a sufficiently reliable analysis vs. having a short time span to enable testing the hypothesis that the factor structure would change relatively quickly. The n-back tasks (i.e., NBD, NBL, NBC, NBB) were divided into blocks of three (3/3/3/3) whereas the other tasks (i.e., the Running Memory tasks RMD and RMB and the Span tasks FSD, FSB, BSD, and BSB) were divided into blocks of one and two (1/2/2/2). Thus, where an even split was impossible, the remaining blocks were included in the last phase. This is motivated by the assumption that most changes in cognitive processing happen at the initial stages of task performance (Chein & Schneider, 2012). The dependent variable for the n-back tasks consisted of the average n-back level achieved in the respective task phase. For the Running memory tasks, the dependent variables were calculated by counting the correctly recalled

items in correct position in a sequence, and then averaging the scores over sequences within the respective task phases. For the Span tasks, the dependent variables consisted of the proportion of correctly recalled items in correct order within the respective task phases (i.e., number of correctly recalled items/total number of items).

2.4. Analytical approach

Longitudinal structural equation modeling over the four task phases was conducted using the *lavaan* package version 0.6-9 (Rosseel, 2012) in the R environment version 4.1.1 (R Core Team, 2021) using Rstudio version 2021.9.0.351 integrated development environment (Rstudio Team, 2021). Goodness of fit was evaluated using the model's χ^2 , the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean square error of approximation (RMSEA), and the standardized root mean squared (SRMR). Acceptable model fit was determined by wholistically evaluating the model fit indices, and acceptable values were set using the Little (2013) guidelines of CFI and TLI $\geq .900$, RMSEA and SRMR $\leq .080$. Item reliability was evaluated using McDonald's ω coefficient (McDonald, 1999). McDonald's ω coefficient can be interpreted using the same heuristics of Cronbach's α coefficient and reports the proportion of variance in common among the items as part of the total observed variance. Measurement invariance was evaluated using the change in CFI of $< .01$ (Cheung & Rensvold, 2002; Little, 2013), and tests of latent parameter differences were evaluated using the χ^2 difference test at an alpha level of .05 to determine significance.

The analysis proceeded in two stages, first determining measurement invariance, and then examining how correlations between the latent factors change over time. Invariance testing establishes whether or not the items being used are psychometrically equivalent at each time point, allowing us to conclude that any changes in the constructs are changes in the constructs themselves and not changes in the measures being used. It is noteworthy that although the skill learning hypothesis implies a change in latent factor structure over time from general to task-specific, testing this hypothesis requires measurement invariance, which is a prerequisite for examining changes in factor intercorrelations (Little, 2013).

2.5. Results

The data were screened to identify univariate outliers (i.e., scores deviating > 3.5 SDs from the sample mean on each task); task performances exceeding this threshold were treated as missing. Moreover, performances from participants who reported being color-blind were treated as missing in the color tasks. The dataset consisted of 296 individuals observed across four time points during each WM task and missingness across all time points ranged from zero to six observations (2%) for any one variable. Our model was estimated using full information maximum likelihood (FIML) to estimate parameters that accounted for the missing observations. Since our models utilized all variables in the dataset, there were no auxiliary variables to specify. Descriptive statistics and pairwise correlations between tasks are summarized in Supplementary Materials, Appendix A.

The first analytical aim was to establish measurement invariance. Our initial CFA configural model for Experiment 1 demonstrated good fit based on our established criteria with a χ^2 of 720.448 ($df = 618$), p -value of .003, CFI of 0.980, TLI of 0.975, SRMR of 0.046, and RMSEA of 0.024 with a 90% confidence interval of (0.015, 0.031). For this measurement

model, reliability for the *N-back* over the four time points was 0.48, 0.79, 0.86, and 0.88. The reliability for *Span* over the four time points was 0.31, 0.53, 0.60, and 0.59. Finally, the reliability for *Running Memory* over the four time points was 0.23, 0.23, 0.32, and 0.31. Although some of these reliability estimates are low, the loadings for all constructs were significant, allowing comparisons of the factor structure in the disattenuated latent space (Little, Lindenberger, & Nesselroade, 1999). This model was evaluated for weak invariance by constraining the item loadings to be equal across time, and then strong invariance by constraining the item loadings and intercepts to be equal across time. Both tests of invariance passed, with a resulting strong model that demonstrated good model fit with a χ^2 of 778.985 ($df = 656$), p -value of .001, CFI of 0.976, TLI of 0.972, SRMR of 0.050, and RMSEA of 0.025 with a 90% confidence interval of (0.017, 0.032). Fit indices for all levels of invariance can be found in Table R11.

After establishing strong invariance, we evaluated the variances and covariances of our latent constructs to assess how these constructs behaved over time. We evaluated whether our paradigm-specific latent factors differentiated at any single time point by constraining their correlations to be 1.0 at that time point and conducting a nested-model χ^2 test to see whether this constraint worsens model fit. With the same method, we also examined whether the intercorrelations of the paradigm-specific latent factors could be constrained to be equal across time points. Failure to do so would indicate that the correlations change over time. To evaluate correlations on the same scale, rescaling constructs were used to estimate standardized covariances among all latent constructs (Little, Slegers, & Card, 2006). Rescaling constructs consist of a standardized latent construct that is modeled with a single factor loading onto the original unscaled construct and all covariance relationships among the unscaled constructs are moved to be between the standardized scaled constructs. This allows for the variance of the unscaled constructs to be estimated on the factor loading, and all of the covariance relationships among the rescaling constructs to be estimated in a correlational metric that can be compared across the different time points.

The final constrained values for the variances and intercorrelations of our latent parameters can be found on Table R12, where an asterisk (*) indicates that a parameter has been constrained to be equal to one or to another parameter within time, and a cross (†) indicates that a parameter has been constrained to be equal with another parameter over time. Based on the hypotheses, we expected that at the initial time point, the paradigm-specific factors can be constrained to correlate at one and behave as a single construct, and then differentiate over time, indicated by a failure to constrain the correlations to be equal across time. Additionally, were constrained to be equal to another within time (even when the correlation is not one) to indicate when the correlations were equidistant, and to see if a relationship that was constrained to be equal at one time point is no longer equal at another time point.

The analyses showed that all three paradigm-specific constructs were undifferentiated at the first time point, as all the factor correlations could be constrained to one. *Running Memory* and *Span* continued to be undifferentiated at the second and third time points, and *n-back* was strongly correlated with this combined construct at time point two ($r = 0.721$) and three ($r = 0.721$). However, while all paradigm-specific constructs remained highly correlated by the fourth time point, they demonstrated differentiation by no longer having a correlation

of 1.0, instead all of them were correlated with each other at $r = 0.721$. This decline in the factor correlations was statistically significant, as shown by the failure to constrain the factor correlations to be equal over time (see Table R12). Only the correlation between *Running Memory* and *Span* remained static at one until the third time point, while all other correlations significantly decreased from one already at the second time point. After the initial drop in the correlations, most remained stable at .721 at the subsequent time points, indicating that the change from unity to diversity mainly took place at the very early phases of task performance.

We also evaluated construct variances over time using this same method to attain the most parsimonious model of the variances and covariances possible. We determined that the variance (i.e., standard deviation) of *Running Memory* and *Span* did not change over time, with *Running Memory* having a variance of 0.493 and *Span* having a variance of 0.128 at all four time points. The *n-back* construct, however, demonstrated a pattern of increased variance over time, with variances of 0.147, 0.614, 0.841, and 0.948, respectively. This indicates increasingly divergent performances in the adaptive task paradigm, i.e., *n-back*. The variances and latent mean scores are summarized in Table R12.

The final model was constructed with the variance and covariance restrictions in place, and demonstrated good overall model fit, with a χ^2 of 795.043 ($df = 673$), p -value of .001, CFI of 0.976, TLI of 0.973, SRMR of 0.052, and RMSEA of 0.025 with a 90% confidence interval of (0.017, 0.031). A nested χ^2 test comparing this constrained model to the strong invariance model demonstrated that this final model did not fit significantly worse than the unconstrained strong invariant model, $\Delta\chi^2 = 16.058$, $\Delta df = 17$, $p = 0.520$. This indicates that our final model, being constrained to reflect the unity-to-diversity pattern in factor intercorrelations, provided an equally good fit to the data as the unconstrained model. A full table of the nested model test results can be found on Table R11, and the final constrained values for the variance and correlation of our latent parameters can be found on Table R12. All the factor loadings over time are presented in Appendix D.

2.6. Discussion

According to skill learning theory (e.g., Chein & Schneider, 2012), task-general metacognitive processes such as strategy generation and cognitive control should play a central role at the initial phases of task performance, whereas at later phases task performance becomes partially automatized through task-specific subroutines. In line with this account, the results show a unity-to-diversity pattern: performances at the initial phase form a single, general factor, but then diverge into factors specific to the task paradigm. A limitation that needs to be carried in mind is that the results are based on individual differences and thus do not afford direct inferences about the underlying cognitive processes. Nevertheless, the findings are consistent with the skill learning theory which entails that a cognitive task does not measure the same construct in the beginning of the task as it does in the later stages. The change in the latent factor structure challenges the common assumption that cognitive tasks measure static constructs.

3. Experiment 2

To replicate the analyses with another dataset, we ran them with the pretest results from our most recent WM training study. The data used in the analyses is available at <https://osf.io/gvqhu/>.

3.1. Participants and procedure

The data of Experiment 2 stems from the pretest of a randomized controlled online trial on working memory training (Ritakallio et al., 2022). The study was approved by the Institutional Review Board of the Departments of Psychology and Logopedics, Åbo Akademi University, and it was conducted in accordance with the Helsinki Declaration. Following an extensive two-step prescreening procedure, 250 participants were invited to take part in the study through Prolific Academic (<https://www.prolific.co/>). Of those, 34 participants did not complete the entire pretest, and an additional 15 participants reported cheating during task performance. This resulted in a final sample size of 201 participants that met our inclusion criteria, which were similar to those in Experiment 1 (i.e., English native speakers, no current psychiatric or neurological illnesses that affected the participant's daily life, no current use of central nervous system (CNS) medication, and no current psychotropic drug use except for tobacco, alcohol, and cannabis). The participants were 18–50 years old with a mean age of 32.09 (SD = 8.27) and 56.5% ($n = 114$) of them were females. The mean education length was 16.13 years (SD = 3.35).

3.2. Materials

The seven WM tasks included in the pre-test battery encompassed three n-back tasks (digits, letters, and colors), two Running memory tasks (letters and colors), two simple span tasks (letters and colors), and two Selective Updating tasks (digits and colors).

N-back paradigm. We administered an n-back task with digits (NBD), letters (NBL) and colors (NBC). The items in each n-back variant were presented identically to those in Experiment 1, and the length was also the same. As in Experiment 1, there were no practice rounds.

Running memory. We administered two Running memory tasks, one with letters as stimuli (RML), and the other with colors (RMC). In both variants, stimulus presentation time was 1000 milliseconds with interstimulus interval at 500 milliseconds. The sequence lengths ranged from 4 to 11 items in both RML and RMC, and the item sequences were presented in a randomized order. The participants completed one trial of each sequence length. The length of these tasks was ca 5 minutes each. The practice rounds were analogous to the Running memory tasks in Experiment 1.

Span. We administered two Forward simple span tasks, one with letters as stimuli (FSL), and the other with colors as stimuli (FSC). In both variants, participants are prompted with a sequence of items (presentation time 1000 milliseconds, interstimulus interval 500 ms), and the task is to recall the items in the order in which they were presented. The sequence lengths ranged from 4 to 9 in the FSL variant, and 4 to 10 in the FSC variant, and the item sequences were presented in a randomized order. The participants completed one trial of each sequence length. The length of these tasks was ca 5 minutes each. The practice trials were analogous to the Span tasks in Experiment 1.

Selective updating. The Selective updating (SU) paradigm builds upon the task introduced by Murty et al. (2011). In this study, we administered two task variants, one with digits (1 to 9) as stimuli (SUD) and one with colors (blue, yellow, red, green, purple, black, pink, orange, and gray) as stimuli (SUC). Besides materials, SUD and SUC were identical to each other (thus, the word ‘item’ pertains to both variants hereafter in the task description). In both tasks, five unrelated items were presented on the computer screen in a row of five boxes. The participants were instructed to memorize the item sequence. After this, the initial item sequence disappeared after which a new row of five boxes was displayed. Two of the new boxes contained new items, while three were empty. The participants were prompted to replace the old items with the items presented most recently in the memorized sequence, while maintaining the unchanged items in WM. In both SUD, and SUC, the participants completed 10 baseline trials (i.e., no updating stages), and 10 trials with three updating stages (i.e., replacement of old items with new ones). The participants were instructed to report the final item sequence. The order of the sequences was randomized, and the participants were unaware whether the next sequence would be a baseline sequence or an updating sequence. The initial item sequence was shown for 4000 milliseconds (SUD) or 7000 milliseconds (SUC), followed by a 100-millisecond blank screen, after which the first updating stage was presented for 2000 milliseconds (SUD) or 5000 milliseconds (SUC). The updating stage was once again followed by a 100-millisecond blank screen and the next updating stage. After all the updating stages had been presented (none in the baseline condition), a recall grid with horizontally aligned boxes containing the numbers from 1 to 9 (or the nine colors) appeared on-screen. The participants were to click on the numbers (or colors) in correct order (see [Fellman et al., 2018; Laine et al., 2018] for more technical details). The length of these tasks was ca 8 minutes each. The practice trials were analogous to the Span tasks. There were three to seven practice trials that consisted of updating sequences and baseline sequences, presented alternately. The first updating sequences were easy, with the updating locations mainly in the beginning or end of the sequence. If the participant correctly answered two consecutive easy sequences, they proceeded to a more difficult sequence where the updating locations were mainly in the middle of the sequence. After that, they proceeded to the actual task, irrespective of whether the last, more difficult sequence was answered correctly.

3.3. Dependent variables

As in Experiment 1, we split the sequences into four phases, roughly matched by length. The number of blocks in the phases were as follows: 3/3/3/3 in n-back (i.e., NBD, NBL, NBC); 1/2/2/2 in Running memory (i.e., RML and RMC), 1/1/2/2 in FSL, 1/2/2/2 in FSC, and 2/2/3/3 in the Selective updating tasks (i.e., SUD and SUC). The dependent variable for the n-back tasks consisted of the average n-back level achieved in the respective task phase. For the Span tasks, the dependent variables consisted of the proportion of correctly recalled items in correct serial order within the respective task phases (i.e., number of correctly recalled items/Total number of items). For the Running memory tasks and the Selective Updating tasks (including only the updating trials), the dependent variables were calculated by counting the correctly recalled items in correct position in a sequence, and then averaging the scores over sequences within the respective task phases.

3.4. Analytical approach

We employed the same analysis method and fit indices criteria as in Experiment 1.

3.5. Results

The data were screened to identify univariate outliers (i.e., scores deviating > 3.5 SDs from the sample mean on each task); task performances exceeding this threshold were treated as missing. Moreover, performances from participants who reported being color-blind were treated as missing in the color tasks. Missingness across all time points ranged from zero to six observations (3%) for any one variable. Descriptive statistics and pairwise correlations between tasks are summarized in Supplementary Materials, Appendix B.

The first analytical aim was to establish factorial invariance. Our initial CFA configural model for Experiment 2 demonstrated good fit based on our established criteria with a χ^2 of 531.918 ($df = 432$), p -value of .001, CFI of 0.975, TLI of 0.964, SRMR of 0.053, and RMSEA of 0.034 with a 90% confidence interval of (0.023, 0.043). For this measurement model, reliability for the *N-back* over our four time points was 0.74, 0.63, 0.79, and 0.84. The reliability for *Span* over our four time points was 0.27, 0.49, 0.46, and 0.41. The reliability for *Selective Updating* over our four time points was 0.56, 0.51, 0.73, and 0.70. Finally, the reliability for *Running Memory* over our four time points was 0.19, 0.34, 0.48, and 0.55. As before, despite low reliabilities, all factor loadings were significant, allowing comparisons in the disattenuated latent space (Little et al., 1999). This model was evaluated for weak invariance by constraining the item loadings to be equal across time, however this model demonstrated too great a change in CFI (Δ CFI = 0.04). We then fit a partial weak invariant model by allowing the loadings for *N-back* to be freely estimated at the initial measurement phase but constraining all subsequent measurement phase loadings to be equivalent. This partially invariant model passed our criteria with a change in CFI of -0.001. We then evaluated strong invariance by constraining the item intercepts to be equivalent over time, however this model also demonstrated too great a change in CFI compared to the partial weak model (Δ CFI = 0.03). After evaluating our item intercepts, we allowed the intercepts for *N-back* at the initial phase to be freely estimated while continuing to constrain all subsequent intercepts to be equivalent over time. The resulting strong model demonstrated good model fit with a χ^2 of 547.879 ($df = 446$), p -value of .001, CFI of 0.975, TLI of 0.964, SRMR of 0.049, and RMSEA of 0.034 with a 90% confidence interval of (0.023, 0.043). Fit indices for all levels of invariance can be found in Table R21.

After establishing partial strong invariance, we evaluated the variances and covariances of our paradigm-specific latent factors to assess how they behaved over time. We once again evaluated whether the paradigm-specific factors were differentiated at any single time point by constraining their correlations to be one and conducting a nested-model χ^2 test to see if the constraint worsens model fit. We also examined whether it is possible to constrain the intercorrelations of the factors to be equal across time to see if there is a change in the latent factor structure from unity to diversity. Finally, as in Experiment 1, factor intercorrelations within a time point were constrained to be equal, when possible, to ease interpretation. To evaluate correlations on the same scale, rescaling constructs were once again used to estimate standardized covariances among all latent constructs (Little 2013).

This method showed that at the initial time point, *Running Memory*, *Span*, and *Selective Updating* were behaving as a singular construct with correlations that could be constrained to one, with *n-back* weakly correlated with *Running Memory* ($r = 0.198$) and moderately correlated with *Span* and *Selective Updating* ($r = 0.456$). At the second time point, *Running Memory* and *Selective Updating* were still undifferentiated with a correlation that could be constrained to one, however the correlations among *Span* and *Running Memory* had become moderate at 0.544, and among *Span* and *Selective Updating* at 0.457. By the third time point, the constructs had completely differentiated, with the correlations between *Running Memory* and *Span*, and *Running Memory* and *Selective Updating* both being 0.781, the correlation between *Selective Updating* and *Span* being 0.610, and all correlations between *n-back* and the other constructs being estimated at 0.457. At the final time point, the differentiation among the constructs continued with the correlations among *Selective Updating*, *Span*, and *Running Memory* being 0.781, and the correlation with all three of these constructs with *n-back* being .457. The decline in the intercorrelations between the paradigm-specific factors was significant, as indicated by the failure to constrain the across time correlations to be equal (see Table R22, where across-time constraints have been marked with the cross symbol). However, in the *n-back* factor there was no clear pattern in the evolvement of correlations with the other paradigm-specific factors. As shown by Table R22, after the initial drop in the factor intercorrelations from the first to the second time point, the correlations mainly did not change between the third and fourth measurement phases, indicating that the latent factor structure becomes more stable after the initial drop in the intercorrelations between the paradigm-specific factors.

To attain the most parsimonious final model, we also evaluated construct variance over time using this same method and determined that the variance (i.e., standard deviation) of *Running Memory* was 0.581 over all time points. The variance of *Span* was 0.138 at the first, third, and fourth time point and increasing to 0.173 on the second. The variance of *Selective Updating* was 0.716 for the first two time points, and 0.876 on the last two. The variance of *n-back* increased at every time point, with the first being 0.324, followed by 0.493, 0.875, and finally 1.060. The latent construct means are reported in Table R22. Again, it was the adaptive task paradigm (*n-back*) in which performances were increasingly diverging over the test session.

The final model was constructed with the variance and covariance restrictions in place, and demonstrated good overall model fit, with a χ^2 of 563.621 ($df = 470$), p -value of .002, CFI of 0.977, TLI of 0.969, SRMR of 0.056, and RMSEA of 0.031 with a 90% confidence interval of (0.020, 0.041). A nested χ^2 test comparing this model to the strong invariance model demonstrated that this final model did not fit significantly worse than the unconstrained strong invariant model, $\Delta\chi^2 = 15.741$, $\Delta df = 24$, $p = 0.897$. This indicates that constraining the correlations to manifest the unity-to-diversity pattern in the way described above fits the data equally well as the unconstrained model. A full table of nested model test results can be found on Table R21, and the final constrained values for the variance and correlation of our latent parameters can be found on Table R22. All the factor loadings over time are presented in Appendix D.

3.6. Discussion

Experiment 2 mostly replicated the results of Experiment 1 with new participants and with a slightly different set of WM tasks. All the task performances, except for the n-back task, formed a single general factor at the outset, and the diversity of the latent paradigm-specific factors increased over time, thus partly replicating Experiment 1.

There are several possible explanations which may have produced the different results for n-back across the two experiments. One potential reason for this is the difference in the tasks between the two experiments. Whereas in Experiment 1 each task type included spatial stimuli, in Experiment 2 no spatial stimuli were included. There is evidence that spatial tasks rely more on executive processes than do verbal tasks, which could be reflected as higher latent correlations in Experiment 1 (e.g., Miyake, Friedman, Rettinger, Shah, & Hegarty, 2001). However, this does not imply that the general factor would be solely driven by the spatial tasks in Experiment 1, because that would have led to the lack of unity in Experiment 2, which did not include spatial tasks. Instead, inclusion of the spatial tasks could enhance initial task loadings on general executive processes.

4. Post hoc analyses

A general issue with both the experiments is that, unlike the other tasks, n-back was adaptive, with the difficulty level being adjusted depending on the performance level of the participant. It is unclear how this might have affected the results. Thus, we ran the analyses with the same method as reported above, but without the n-back task.

In the case of Experiment 1, the original results were not fully replicated, and the remaining tasks *Running Memory* and *Span* showed a pattern of correlation from .898 through 1.0 in the second and third phases to .806 in the last phase. Thus, although the correlations were strong at the initial time points and weakest (but still strong) at the last time point, in line with the hypotheses, they could not be constrained to perfect unity at the initial phase. However, in Experiment 2 where the original analyses failed to show a fully consistent unity-to-diversity pattern, this pattern was observed when n-back was left out of the analysis. All the remaining tasks *Running Memory*, *Span*, and *Selective Updating* could be constrained to correlate at one at the initial stage, but at the second stage the correlation between *Running Memory* and *Span* dropped to .417, and between *Span* and *Selective Updating* to .449. At the third and fourth time points, all constructs had become differentiated with moderate-to-strong correlations. As in the original analyses, these changes in the strength of the correlations were significant, as manifested by the failure to constrain them to be equal over time. Full tables of nested model test results as well as the final constrained variance and correlation matrices of the latent parameters for both experiments without n-back can be found in Appendix C.

5. General discussion

The present study addressed a fundamental assumption in cognitive testing, namely that the cognitive processes underlying complex task performance remain static throughout the whole task. In contrast, cognitive skill learning literature implies that performing a task is an adaptive learning process that proceeds from task-general metacognitive and control processes to more automatic and task-specific ones (Ackerman, 1988; Chein & Schneider, 2012; Schneider & Chein, 2003; Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977). Here we applied this approach for the first time to widely used WM tasks, during the time

course of only a few minutes. The results from the two independent data sets analyzed in Experiments 1 and 2 were mostly consistent with the skill learning hypothesis in that the latent task factors (except for n-back in Experiment 2) were perfectly correlated in the beginning of the tasks but differentiated at later stages.

In line with the skill learning theory, the findings could reflect a change from task-general metacognitive and control processes to more task-specific ones. It appears that in the present WM tasks, the task-general phase is quite short-lived, as the paradigm-specific factors were undifferentiated only at the initial task phase, showing diversification thereon. This is supported by independent evidence from our two previous microgenetic studies that focused on strategy use in memory tasks (Waris et al., 2020, 2021). These previous results show that changes in strategies take place mainly during the first 2-3 blocks of a task, which indicates short-lived metacognitive and control processing. After the first blocks, use of memory strategies becomes more stable while performance is steadily enhanced. This could reflect increased routine in the employment of the strategies.

The results of the present experiments can be compared to those of a previous study that tested the skill learning hypothesis with WM training data (Meiran, Dreisbach, & von Bastian, 2019). In line with the present results, they found a pre-post decrease in the correlation between their WM-related latent factors binding and updating (from .91 to .75; see Figure 3 in De Simoni & von Bastian, 2018). Interestingly, at the same time their adaptive WM training tasks maintained or even increased their correlations with general intelligence (measured by reasoning tasks) when the training progressed. These results point to a dissociation in the evolvement of WM task intercorrelations vs. WM task – IQ measure correlations following repeated adaptive WM practice. However, one should be cautious in drawing parallels between these two studies, as their time scales are very different (minutes vs. weeks), and our study did not employ separate measures of intelligence.

4.1. Limitations

An important limitation is that our analytical method (LSEM), which is based on individual differences, only yields indirect evidence of the processes underlying task performance. Based on the skill learning theory, we assume that unity in the latent factors reflects metacognitive and controlled processes, whereas diversity reflects the buildup of more automatic, task-specific lower-level processes (Chein & Schneider, 2012; Taatgen, 2013). Confirming this presumption would benefit from more direct measures of the underlying processes. As to the hypothesized buildup of automaticity, one possibility could be to follow up the speed of the basic stimulus-response mapping required to perform the task. To take a concrete example, in an experiment consisting of adaptive n-back tasks, one could employ intermittent 1-back blocks that have a minimal WM load and track whether the reaction times are speeded up over the course of the experiment. This could tap on the emergence of task-specific automatic production rules at the sensory-motor level (Taatgen, 2013). Another possible option would be to use a simple intermittent secondary task. Due to the hypothesized initial high executive load on the complex and unfamiliar primary task, the secondary task should create clear interference early on. However, this interference effect should be attenuated over time, reflecting increase in executive resources that are freed for the secondary task.

Another potential limitation relates to probable inter-task and inter-individual differences in when the peak executive load occurs. To take an example of the former, in simple span tasks executive load can be expected to be weaker than in more complex tasks and arguably peaks at an early stage, whereas more complex WM tasks assumedly load on the executive system for a longer period. The length and intensity of these executively taxing task-initial periods may also vary considerably between participants, depending on their individual characteristics. The current analytical method with rough splits of the task periods at a group level does not take these factors into account. Multilevel methods where individual slopes for tasks and participants can be specified could aid in detecting such effects, but to our knowledge this is not possible in latent factor analyses. A related limitation is that the time resolution in our analysis is somewhat coarse. This limitation is due to the use of SEM, which is based on individual differences and requires large datasets.

A technical limitation of the present study pertains to reliability which appeared to be poor for several of the constructs at various time points across both experimental conditions, as assessed using McDonald's omega coefficient. However, while reliability can be informative of the performance of the indicators of a construct, the reliability of the indicator does not dictate that indicator's viability for measuring an underlying construct in an SEM framework (Little et al., 1999). Simulation studies have demonstrated that items with poor psychometric properties such as low reliability can produce accurate estimates of the underlying variance and covariance structure of the latent constructs so long as they sufficiently cover the underlying construct space, yield sufficient variability on the construct as demonstrated by the significance of their loadings, and are analyzed in the context of SEM in order to accurately model and disassociate the reliable variance from the unreliable variance (Little et al., 1999).

The tasks of the present study stemmed from previous cognitive training studies and at least some of them may not be ideal for the present type of analysis. For example, the present n-back tasks were adaptive which lessens the degree to which they can be automatized, we had practice rounds that decreased task novelty prior to the initial measurement phase, and span length variation between trials in the span tasks added variability to the results. Moreover, the length of the tasks varied substantially, with the n-back task being the longest one due to its adaptivity. These factors should be considered in future studies. The fact that the main findings were nevertheless largely replicated in two independent datasets with different sets of tasks speaks for the robustness of the results. Moreover, omitting N-back from the analyses did not substantially change the overall pattern, which became less consistent with the hypotheses in Experiment 1, but more consistent in Experiment 2.

A more specific interpretational difficulty concerns with what the unity in the initial stages reflects. In line with the cognitive skill learning view, we have hypothesized that it reflects the engagement of the metacognitive system (e.g., strategy generation, task initiation and monitoring) and the cognitive control system (e.g., attention allocation and process sequencing for the adopted performance strategies). However, the unity cannot indicate fully shared cognitive processes between the tasks, given their structural differences and different stimulus materials, which necessitate the engagement of task-specific sensory-motor systems right from the outset. It is important to note that a full unity on the level of cognitive processes is not what the present analyses suggest, but instead that the different tasks can be considered

to form a psychometrically unitary construct. This is a general feature of the SEM method and not specific to the present study. For example, verbal and spatial intelligence tasks often form a single construct (e.g., Meiran et al., 2019), but this obviously does not imply that the underlying cognitive processes would be identical.

A related question is what the paradigm-specific factors in the subsequent phases reflect. This cannot be answered based on the present results alone, but it can be hypothesized that they implicate an increasing role of cognitive processes that are specific to the task-structure. This could be explicated in terms of Taatgen's (2013) primitive information processing elements (PRIM) model. Any task typically requires several such elements, whose consecutive performance requires executive control when a task is novel. However, through learning the elements can be clustered into "production rules" which enable effortless and automatic performance of several processing elements in a row (see Figure 3 in Taatgen, 2013). The diversification of the latent constructs into paradigm-specific factors in the present study could reflect such a process. However, the formation of the paradigm-specific factors does not imply that the processes would be identical between the task variants that form the factor, or that the process would be completely automatic. The differences are gradual, not absolute.

4.2. Theoretical and practical implications

Cognitive task performance is an adaptive process. The present results indicate that the skill learning approach is relevant also to psychometric tasks. Even during the short time spans of these tasks, we observed a shift from unity to diversity in the latent factor structure, which could indicate a shift from task-general control and metacognitive processes to more task-specific skills. This interpretation is supported by independent evidence from the recent microgenetic studies by Waris et al. (2020, 2021), which indicate a very early engagement of metacognition and cognitive control in the form of strategy development in memory tasks. Interestingly, this overlaps temporally with the strong latent factor correlations that we observed in the first stage of the present experiments.

The shift from task-general to task-specific processes could apply to any complex cognitive task, not only WM tasks. Of particular interest here are executive functions (EF). In their highly influential study, Miyake and colleagues (2000) divided EF into three latent factors, namely inhibition, shifting, and WM updating/monitoring. Future research should run the present type of analyses with the kinds of tasks Miyake et al. (2000) used. Whereas Miyake et al. employed summative scores and found that the EF system shows both unity and diversity (in that there are separable but correlated factors), we expect that the inclusion of the temporal dimension would reveal a shift from an initially high unity towards diversity as the tasks progress.

Psychometrics should take the temporal dimension of task performance into account. Our results suggest that time-structured intraindividual variability should be taken better into account during cognitive testing, as suggested recently by Gonthier and Roulin (2020). One can speculate whether within-task learning curves and their slopes might be more sensitive measures of individual EF than the currently used summative scores. Other methods to address intraindividual diachronic changes include, for instance, dynamic systems

modeling or statistical methods such as generalized additive mixed models (GAMM; Gonthier & Roulin, 2020).

Different stages of task performance may show variable convergent and ecological validity. If the initial stage of processing provides a purer (i.e., less task-specific) measure of EF, one could ask whether task-initial performance also correlates more strongly with other goal-directed adaptive behaviors than the commonly used summative scores that also encompass later phases of task performance. For instance, the initial stages of WM processing might correlate more strongly with the initial stages of other EF tasks, or with general fluid intelligence measures, than summative scores (for a recent attempt into this direction, see Nordenswan et al., 2020). Due to their higher executive engagement, the initial stages of complex cognitive task performances might also show stronger correlations with measures of everyday behaviors such as academic achievement. These possibilities should be tested further in future research.

Working memory is not just a capacity. From the perspective of WM research particularly, the present results converge with literature that questions a straightforward use of the notion of WM capacity. Even though temporary storage of information must exist already at the physiological level, it is in practice very difficult to tease out this component from related processes such as strategy use that can have a considerable impact on actual WM performance. Thus, we agree with Simmering and Perone (2013) who argue that WM capacity is not capacity in the traditional meaning of the term (e.g., number of slots in a storage system), but the final product of multiple cognitive systems that operate during task performance. Whereas Simmering and Perone (2013) show how WM is dynamic across the human development, our results indicate changes in WM processes even within a single testing session. In contrast to this reasoning, it could be argued that WM capacity is a constant, and that the changes in task performances only reflect differences in how efficiently the capacity is utilized. However, the notions of capacity and utilization efficiency are difficult to experimentally tease apart (von Bastian & Oberauer, 2014).

Behavioral testing partly creates what it measures. In a broader theoretical perspective, the results support the general “Spencerian” hypothesis that cognition is a process that adapts to the context. This implies that cognitive mechanisms may not exist “out there” at the latent level, waiting to be measured. Instead, cognitive testing partly creates what is being measured, as the cognitive system adapts to the test. This is emphasized by theories of situated or embodied cognition (e.g., Anderson, 2014). To illustrate by analogy, we may assume that the brain carries no general schema for loading the dishwasher prior to being exposed to that activity; there is only a general capacity to learn perceptual-motor processes in countless individual instances. Similarly, cognitive task performance might reflect the properties of the task, not a pre-existing cognitive process.

5. Conclusions

The present results challenge the assumption that the human cognitive architecture remains static during the brief time periods (at the level of minutes) that most cognitive tasks take. Using WM tasks, we revealed a shift from task-general to more task-specific processing during the short task periods. This can be conceptualized along the lines of the skill learning theory as a shift from global metacognitive and executive processes to task-specific and more

automatic processes. This implies that what cognitive tasks measure changes over time and motivates a look also at within-task intraindividual variability and learning, and not just the summative measures in cognitive testing. More generally, the results support the view that cognition is an adaptive process that, to paraphrase Spencer, molds into the shape of the environment. It follows that it is impossible to behaviorally measure a cognitive process without affecting it, as the system quickly adapts to the context through learning task-specific skills. A detailed analysis of cognitive task performance as it unfolds over time provides a rich but underutilized source of data that promises to further our understanding on what cognitive tasks measure.

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TABLES AND FIGURES

Table R11: Experiment 1 Measurement Invariance and Nested Model Comparisons

	χ^2	df	p-value	CFI	TLI	RMSEA	SRMR	Δ CFI	$\Delta\chi^2$	Δ df	p-value	Pass?
Configural	720.448	618	0.003	0.98	0.975	0.024	0.046	–	–	–	–	Yes
Weak	743.808	635	0.002	0.979	0.974	0.024	0.049	0.001	23.359	17	0.138	Yes
Strong	778.985	656	0.001	0.976	0.972	0.025	0.05	0.003	35.177	21	0.027	Yes
Lt.Correlation	787.689	667	0.001	0.977	0.973	0.025	0.05	–	8.704	11	0.649	Yes
Lt.Variance	785.938	662	0.001	0.976	0.972	0.025	0.051	–	6.953	6	0.325	Yes
Omnibus	795.043	673	0.001	0.976	0.973	0.025	0.052	–	16.058	17	0.52	Yes

Notes: Measurement invariance was evaluated using the Δ CFI with .01 as the threshold for passing. Latent parameters were tested using nest χ^2 difference tests with an alpha of .05.

Table R12: Experiment 1 Final Parameter Estimates

	Correlations											
	NB T1	RM T1	SP T1	NB T2	RM T2	SP T2	NB T3	RM T3	SP T3	NB T4	RM T4	SP T4
NB T1	1.000											
RM T1	1.000*	1.000										
SP T1	1.000*	1.000*†	1.000									
NB T2	1.010	0.868	0.804	1.000								
RM T2	0.819	1.077	0.957	0.721*†	1.000							
SP T2	0.832	0.919	1.054	0.721*†	1.000*†	1.000						
NB T3	1.002	0.766	0.724	1.010	0.768	0.685	1.000					
RM T3	0.784	1.309	0.842	0.698	1.136	0.868	0.721*†	1.000				
SP T3	0.881	1.028	1.054	0.764	1.146	1.011	0.721*†	1.000*†	1.000			
NB T4	0.995	0.764	0.707	0.997	0.668	0.678	0.994	0.674	0.710	1.000		
RM T4	0.839	0.966	0.830	0.722	1.175	0.988	0.725	0.908	0.850	0.721*†	1.000	
SP T4	0.973	1.055	1.030	0.808	0.919	1.022	0.728	0.908	1.079	0.721*†	0.721*	1.000
Means	1.631	2.383	0.689	2.508	2.433	0.675	2.700	2.562	0.670	2.795	2.522	0.663
S.D.	0.147	0.493†	0.128†	0.614	0.493†	0.128†	0.841	0.493†	0.128†	0.948	0.493†	0.128†

Notes: Parameters marked with an asterisk (*) are constrained to be equal to one or another parameter within time, and parameters marked with a cross (†) are constrained across time. As a rule of thumb, the absence of cross symbol indicates a significant change between the time points, i.e., in those case constraining the factor correlations to be equal over time has resulted in significantly worse model fit.

Table R21: Experiment 2 Measurement Invariance and Nested Model Comparisons

	χ^2	df	p-value	CFI	TLI	RMSEA	SRMR	Δ CFI	$\Delta\chi^2$	Δ df	p-value	Pass?
Configural	531.918	432	0.001	0.975	0.964	0.034	0.053	—	—	—	—	Yes
Weak	709.532	435	0.000	0.932	0.901	0.056	0.113	0.043	177.615	3	0.000	No
Weak Partial	528.366	433	0.001	0.976	0.966	0.033	0.051	0.001	-3.551	1	1.000	Yes
Strong	658.934	448	0.000	0.948	0.926	0.048	0.083	0.029	130.567	15	0.000	No
Strong Partial	547.879	446	0.001	0.975	0.964	0.034	0.049	0.002	19.513	13	0.108	Yes
Lt.Correlation	555.283	462	0.002	0.977	0.968	0.032	0.052	—	7.404	16	0.965	Yes
Lt.Variance	552.829	453	0.001	0.975	0.966	0.033	0.051	—	4.950	7	0.666	Yes
Omnibus	563.621	470	0.002	0.977	0.969	0.031	0.056	—	15.741	24	0.897	Yes

Notes: Measurement invariance was evaluated using the Δ CFI with .01 as the threshold for passing. Latent parameters were tested using nest χ^2 difference tests with an alpha of .05.

Table R22: Experiment 1 Final Parameter Estimates

Correlations																
	NB T1	RM T1	SP T1	SU T1	NB T2	RM T2	SP T2	SU T2	NB T3	RM T3	SP T3	SU T3	NB T4	RM T4	SP T4	SU T4
NB T1	1.000															
RM T1	0.198	1.000														
SP T1	0.456*	1.000*	1.000													
SU T1	0.456*	1.000*†	1.000*	1.000												
NB T2	1.087	0.186	0.451	0.592	1.000											
RM T2	0.295	1.328	0.881	0.954	0.317*	1.000										
SP T2	0.305	0.704	0.912	0.578	0.317*	0.544*	1.000									
SU T2	0.442	0.962	0.969	1.095	0.544*	1.000*†	0.457*	1.000								
NB T3	1.128	0.196	0.351	0.456	0.989	0.272	0.293	0.462	1.000							
RM T3	0.472	1.021	0.893	0.868	0.518	1.184	0.600	0.868	0.457*†	1.000						
SP T3	0.448	0.965	0.895	0.791	0.532	0.753	0.606	0.629	0.457*†	0.781*†	1.000					
SU T3	0.447	0.726	0.862	1.071	0.510	0.807	0.434	1.147	0.457*†	0.781*†	0.610	1.000				
NB T4	1.162	0.177	0.420	0.441	0.984	0.265	0.313	0.474	1.006	0.463	0.433	0.454	1.000			
RM T4	0.450	1.063	0.637	0.962	0.455	1.029	0.500	0.861	0.474	0.826	0.472	0.789	0.457*†	1.000		
SP T4	0.465	1.116	0.966	1.075	0.550	1.099	0.999	1.006	0.452	0.937	1.078	0.853	0.457*†	0.781*†	1.000	
SU T4	0.443	0.769	0.735	1.070	0.478	0.918	0.405	1.076	0.458	0.825	0.628	1.032	0.457*†	0.781*†	0.781*	1.000
Means	1.836	2.670	0.644	3.025	2.494	2.790	0.635	3.040	2.860	2.776	0.633	3.056	2.990	2.760	0.636	3.087
S.D.	0.324	0.581†	0.138†	0.716†	0.493	0.581†	0.173	0.716†	0.875	0.581†	0.138†	0.876†	1.060	0.581†	0.138†	0.876†

Notes: Parameters marked with an asterisk (*) are constrained to be equal to one or another parameter within time, and parameters marked with a cross (†) are constrained across time. As a rule of thumb, the absence of cross symbol indicates a significant change between the time points, i.e., in those case constraining the factor correlations to be equal over time has resulted in significantly worse model fit.